

Assimilation of passive microwave data in heavy precipitation

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2018Q3 TROPICS Applications Workshop

October 5, 2018



**This work is supported by the NASA Data
for Operation and Assessment program,
grant# NNX17AE89G.
Many thanks to NDOA Program Manager,
Dr. Tsengdar Lee.**

- Due to limitations in directly assimilating microwave cloudy observations in the rain-bands of hurricanes, a new technique named Bayesian Monte Carlo Integration (BMCI) is introduced.
- The BMCI technique is used to retrieve T , q , wind speed and several other parameters from microwave radiances.
- These retrievals can be either directly used by forecasters to evaluate the structure of hurricanes or be assimilated into NWP models.

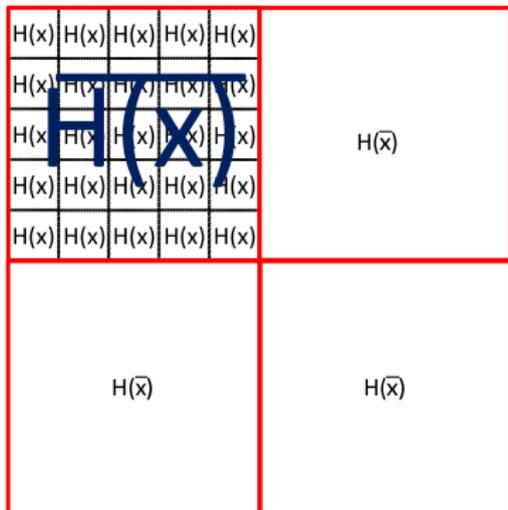


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Assuming Gaussian Errors: DA systems assume Gaussian error statistics, examined using the departures, but in the case of cloudy radiances the departures are likely to be non-Gaussian

The BMCI technique

The BMCI technique can be summarized in three steps:

- generation of a retrieval database of atmospheric state and cloud variables using a-priori information. The database should also include extreme cases as the extrapolation is not allowed.

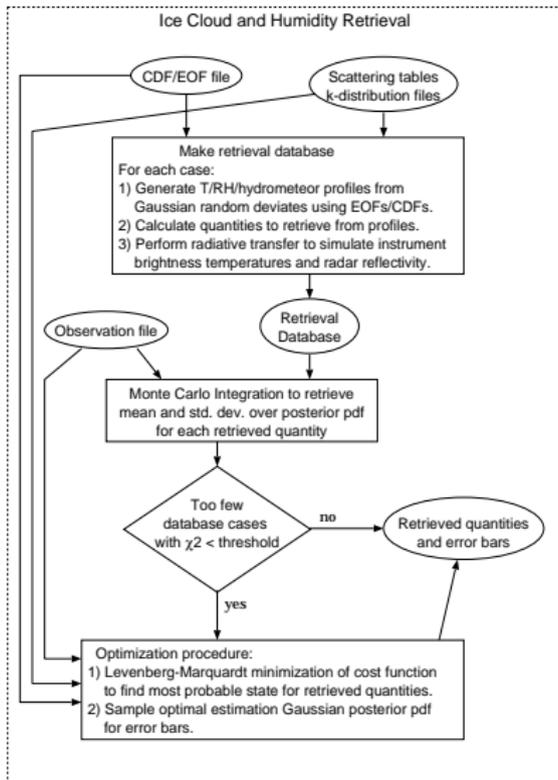
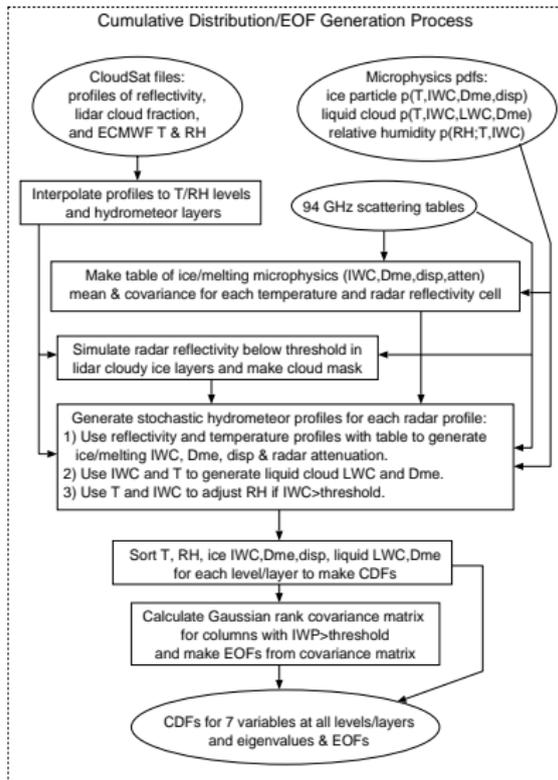
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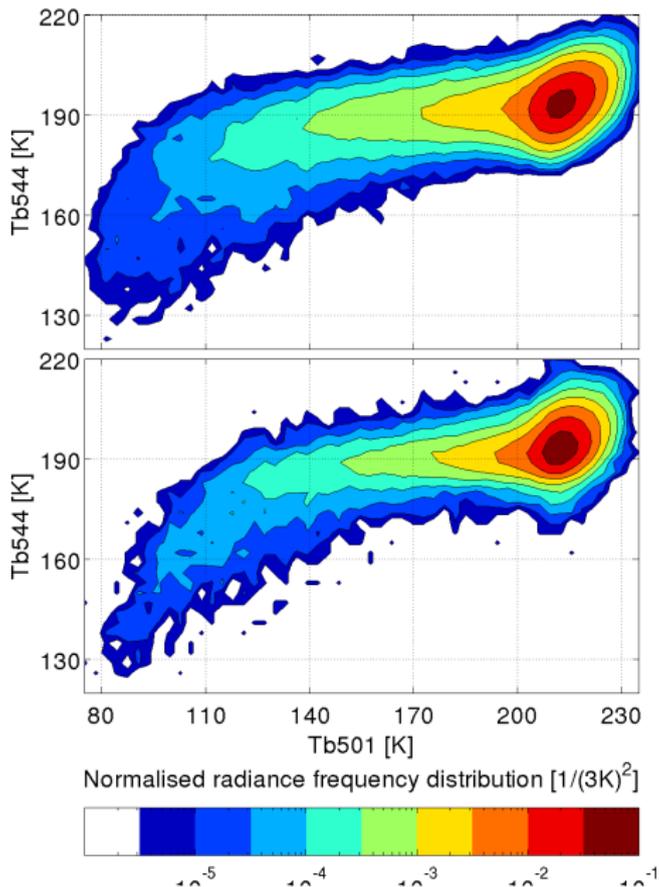
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- real measurements along with the generated database are given to the retrieval package, then the retrieval package will select the cases which are close to the real measurements and integrate them according to the Bayes' theorem to give the estimate of the mean and uncertainty of the state and cloud variables.





Rydberg et al., 2009

$$p_{post}(\vec{x}|\vec{y}) = \frac{p_f(\vec{y}|\vec{x})p_p(\vec{x})}{\int p_f(\vec{y}|\vec{x}')p_p(\vec{x}')d\vec{x}'} \Rightarrow \text{Posterior} = \frac{\text{Likelihood} \times \text{Prior}}{\text{Marginal Likelihood}}$$

The retrieved values for atmospheric or cloud state (\hat{x}) can be computed by integrating over the posterior pdf:

$$\hat{x} = \int \vec{x} p_{post}(\vec{x}|\vec{y}) d\vec{x}$$

$$\hat{x} = \frac{\sum_i x_i p_f(\vec{y}|\vec{x}_i)}{\sum_i p_f(\vec{y}|\vec{x}_i)}$$

The variance (error) of the posterior pdf is calculated as:

$$\sigma_x^2 = \int (x - \hat{x})^2 p_{post}(\vec{x}|\vec{y}) d\vec{x}$$

The conditional pdf can be defined using the probability density of the measured vectors for any given atmospheric state (j channel number):

$$P(\vec{y}|\vec{x}) = \prod_{j=1}^m \frac{1}{\sqrt{2\pi\sigma_j^2}} \exp\left(-\frac{[\vec{y}_j - H_j(\vec{x})]^2}{2\sigma_j^2}\right)$$

σ is the noise in the measurements and \hat{x} now can be calculated as:

$$\hat{x} = \frac{\sum_i \vec{x}_i \exp(-\frac{1}{2}\chi^2)}{\sum_i \exp(-\frac{1}{2}\chi^2)}$$

$$\chi^2 = \sum_{j=1}^M \frac{[\vec{y}_j - H_j(\vec{x})]^2}{\sigma_j^2}$$



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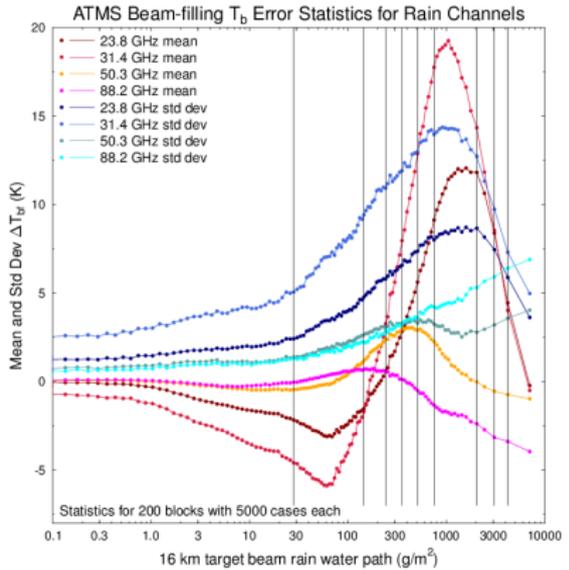
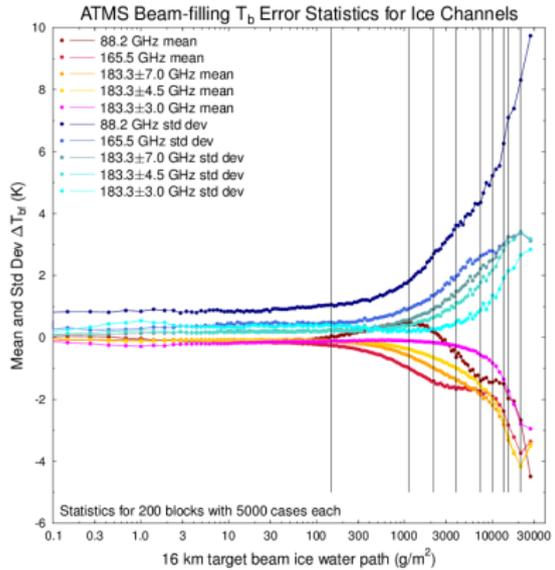
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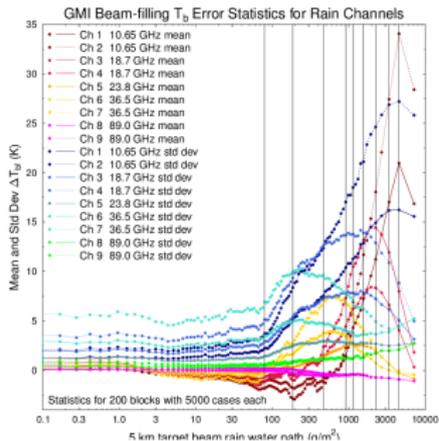
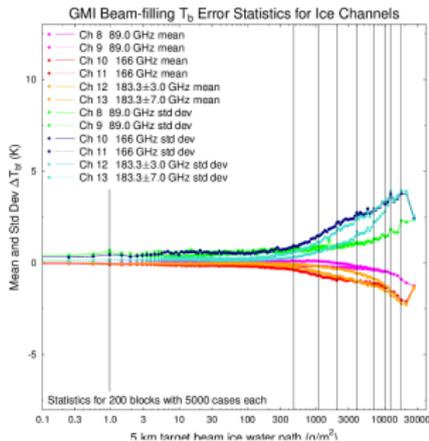
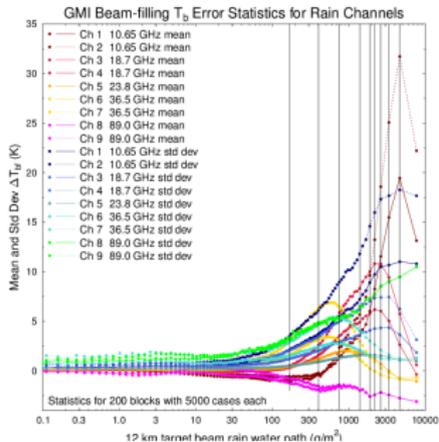
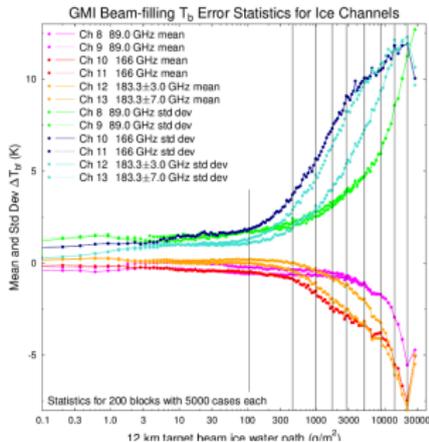


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- Modifying the 1D Bayesian retrieval program to input the new CDF-EOF a priori file and generate consistent profiles of temperature, relative humidity, and ice particle, raindrop, and cloud droplet size distribution parameters to use in the Bayesian profile retrievals.

Beam filling

Beam filling was calculated as the difference between the brightness temperatures weighted according to an elliptical Gaussian beam pattern and T_b s calculated using the average profiles. The profiles were generated with 5km resolution using stochastic statistics derived from GPM DPR and central prof





Hurricane Sandy CloudSat overpassed it on October 27, 2012

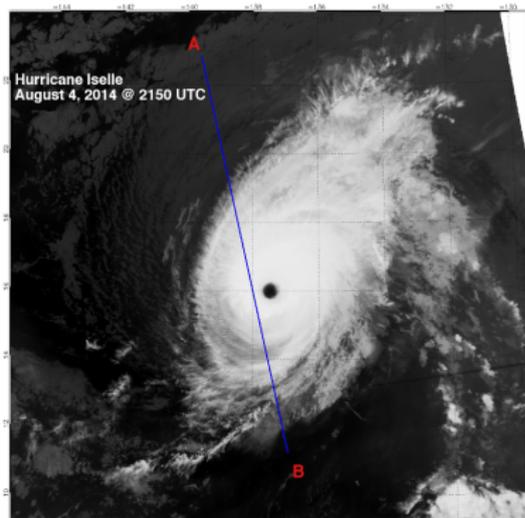
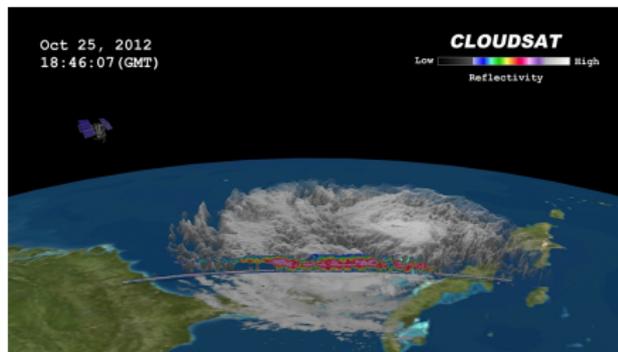
Hurricane Iselle CloudSat overpassed the hurricane on August 4, 2014

Hurricane Amanda CloudSat overpassed Hurricane Amanda on May 25, 2014

Hurricane Joaquin In an early stage of the formation of Hurricane Joaquin, on September 29, 2015, CloudSat passed over the center of the hurricane in the Caribbean.

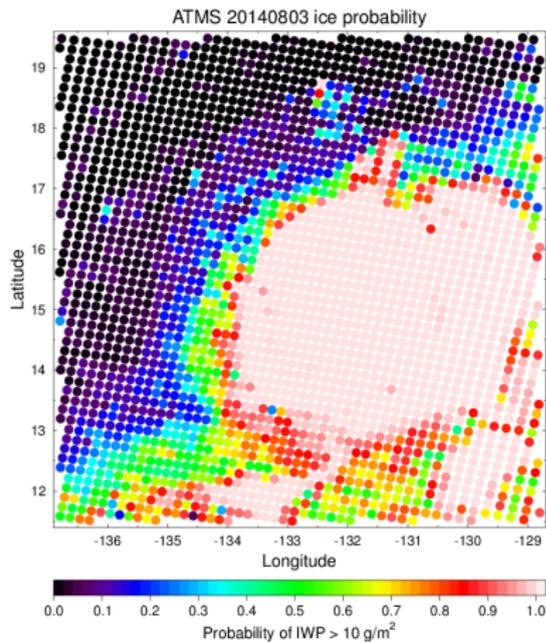
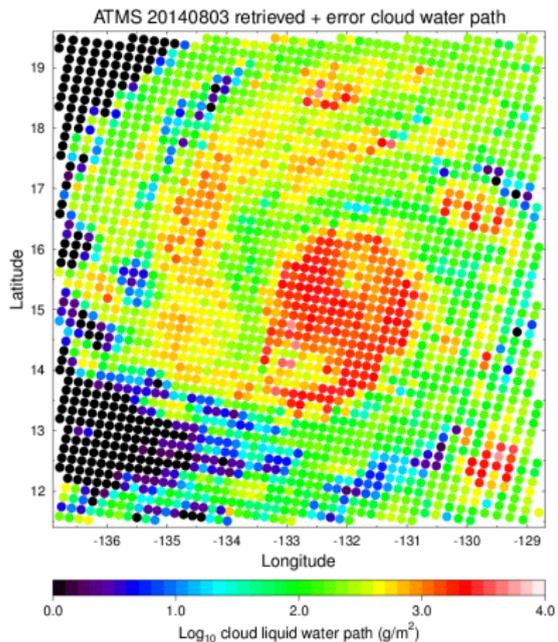
Image credit:

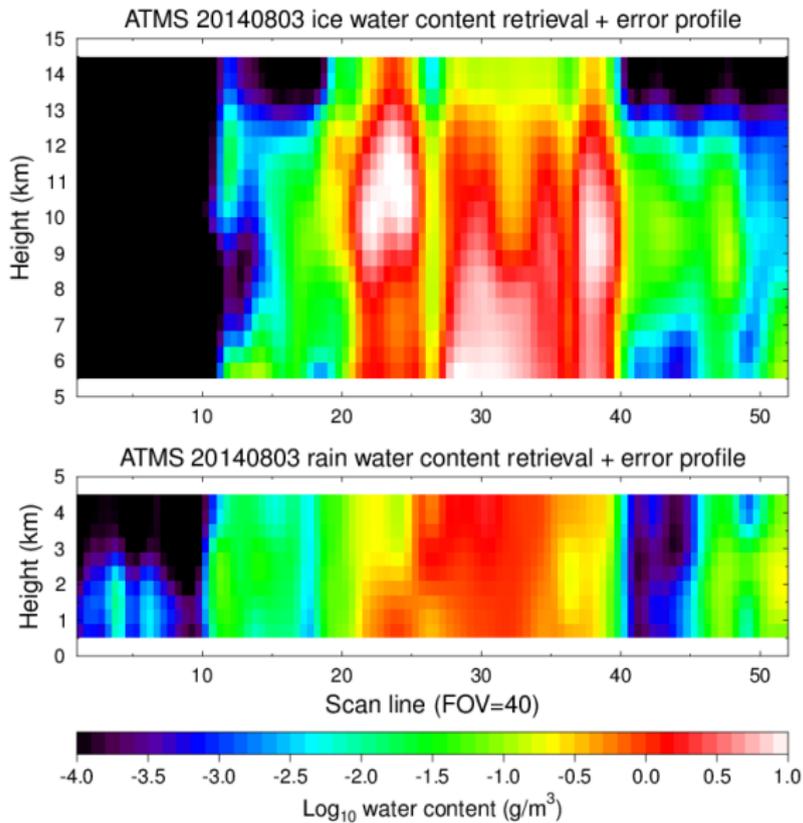
cloudsat.atmos.colostate.edu

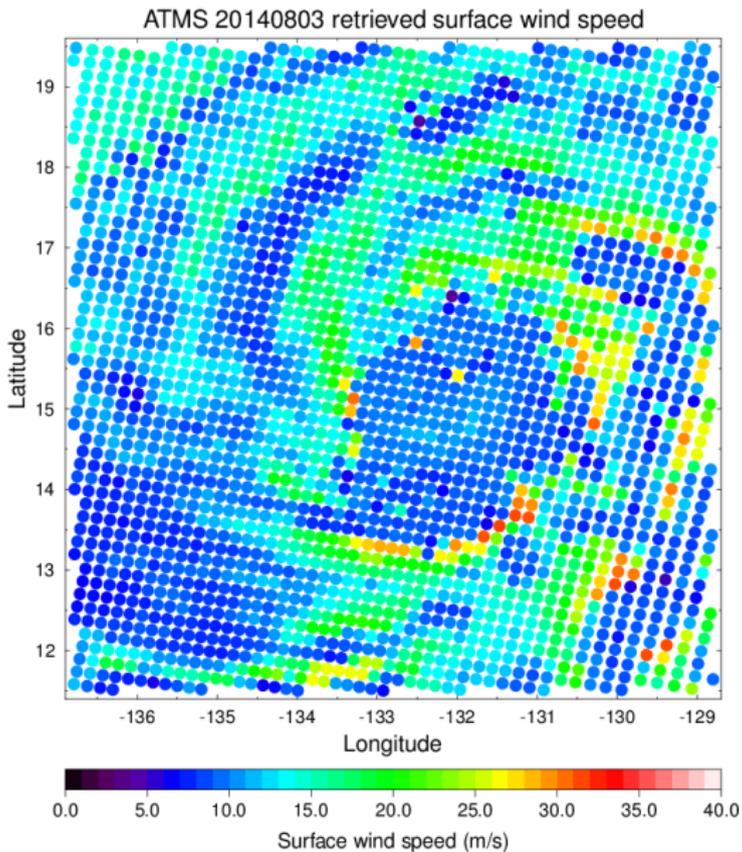


Collocating Satellite and TCVital

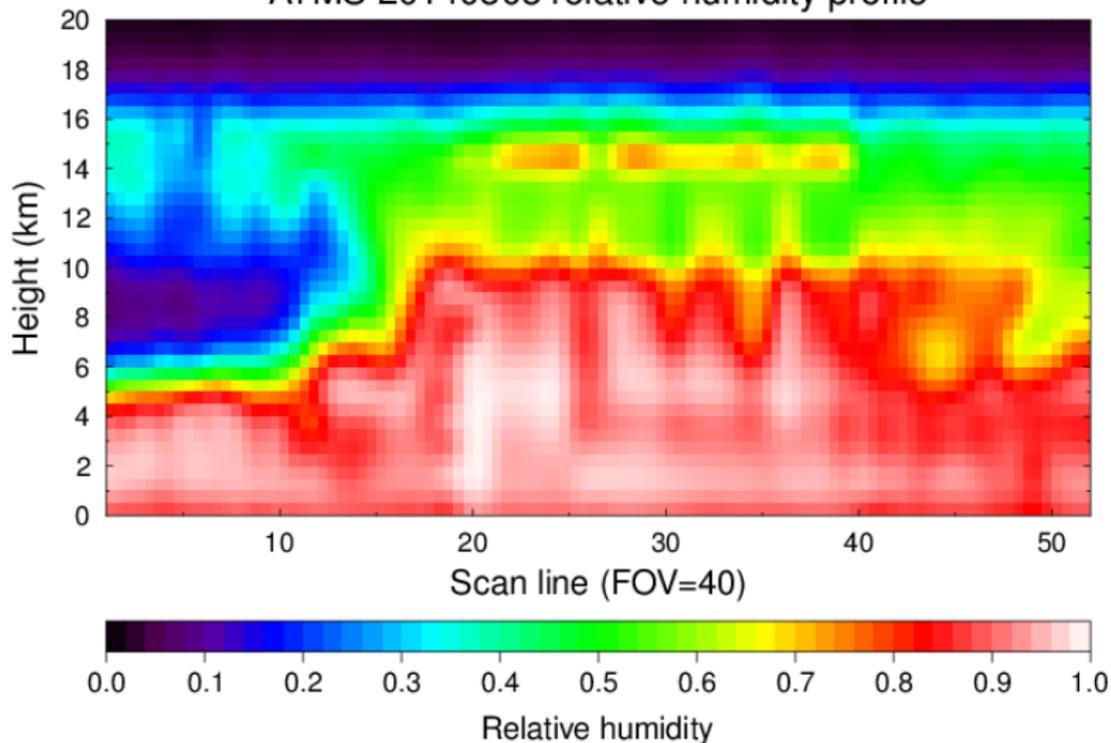






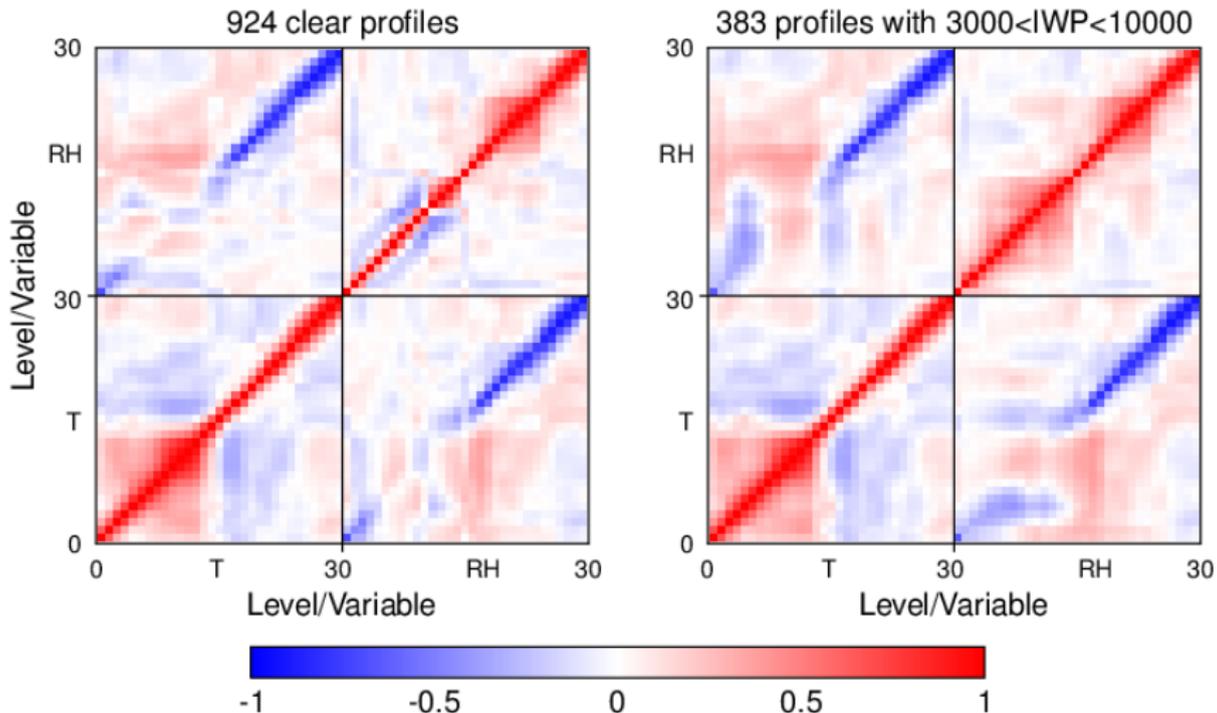


ATMS 20140803 relative humidity profile

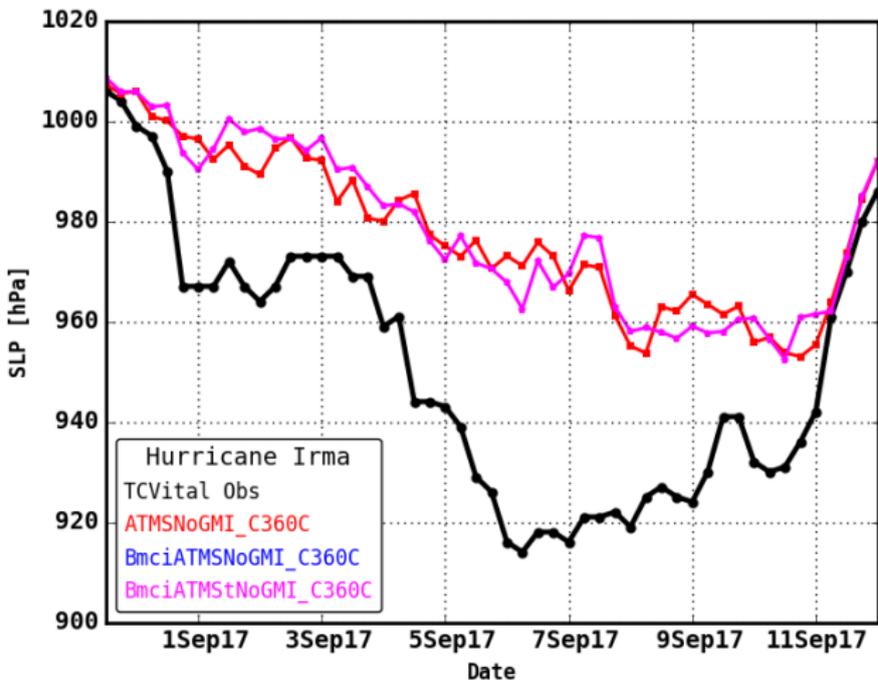


Top: SkinTemp (left), IWP (right), Bottom: Rain WP (left), Surface Wind Speed (right)

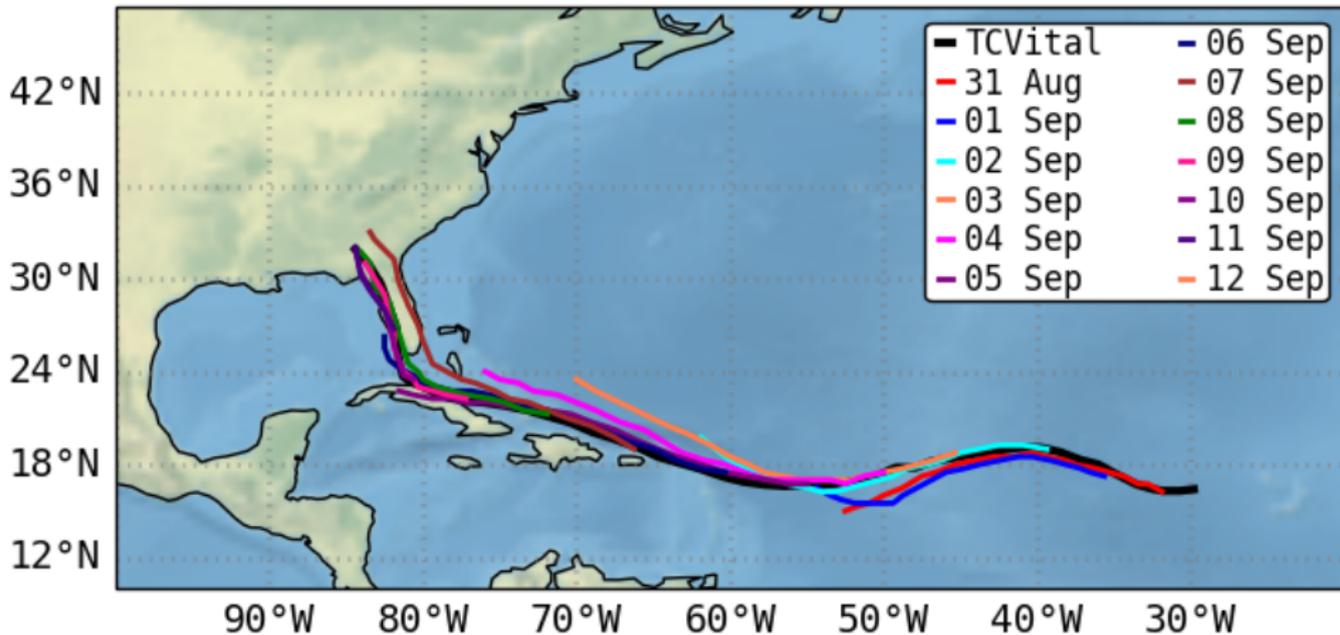
Retrieved Uncertainty Correlation Matrices



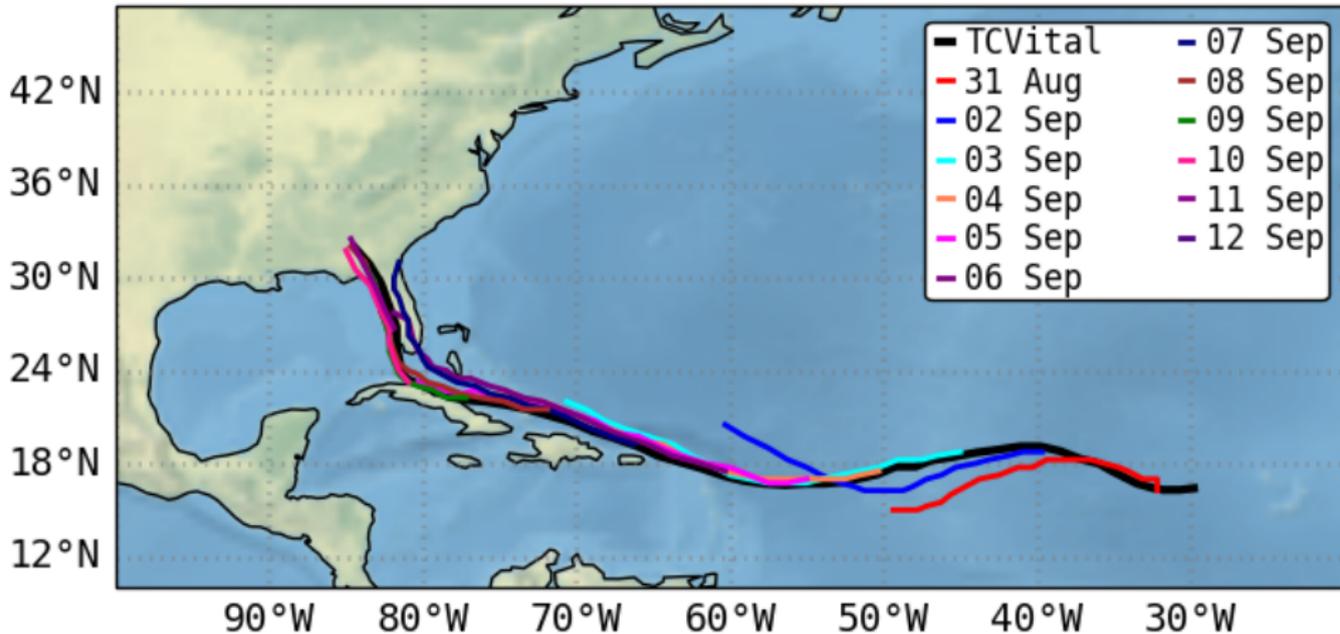
Data Assimilation Results - Intensity



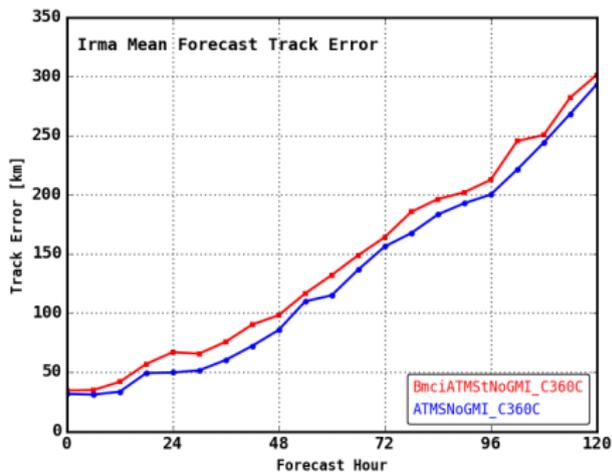
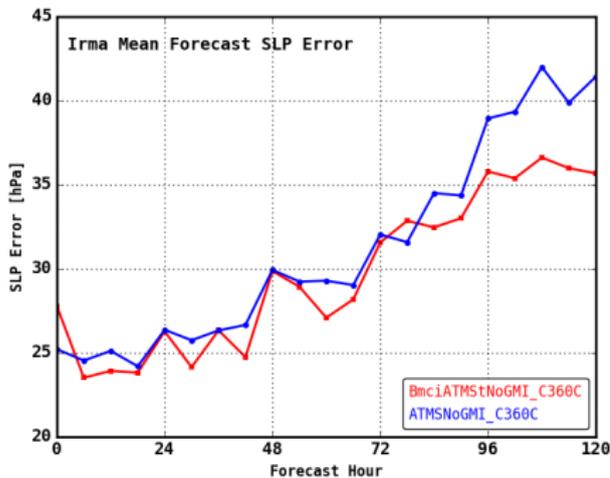
ATMSNoGMI_C360C



BmciATMStNoGMI_C360C



Data Assimilation Results - Track and Intensity Error



- Conventional data assimilation schemes cannot properly assimilate satellite radiances in the rainband of tropical cyclones due to inaccuracy in RT scattering parameters as well as inaccuracy in the first guess provided by NWP models
- A new technique is proposed that does not depend on the minimization of the cost function.
- Preliminary results from BMCI technique are encouraging but require extensive validation, though validation itself is challenging
- These retrieved profiles are valuable for both analyzing the structure of the hurricanes as well as to provide more accurate initial conditions for the NWP models

Thank you for
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